5-26-2017

The Impact of Ride-Hailing Services on Public Transportation Use: A Discontinuity Regression Analysis

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JEL Codes: C21, D22, D43, H41, R40

Abstract
Since 2011, the private ride-hailing companies Uber and Lyft have expanded into more and more US cities. We use regression discontinuity design to examine the impact of Uber and Lyft's entry on public transportation use in the US' largest urban areas. In most cases, entry into cities by the two ride-hailing companies was staggered: Uber entered first followed some months later by Lyft. We find that public transportation use increased in an urban area, all else equal, immediately following the first entry. However, we find that the spike in public transportation use after first entry disappeared following the entry of the second company. In fact there is some evidence that monthly public transportation ridership levels fell below their pre-first entry levels. In other words, the joint presence of the two major private ride-hailing services transformed ride-hailing services from a public transportation complement to a public transportation substitute, at least in the studied urban areas. We speculate that the first entrant complemented public transportation use for some in an urban area by solving the "last-mile" problem and by providing a potentially safer option at night when public transportation service has been reduced. However, we speculate the second entrant is likely to have spurred price competition in the urban area's ride-hailing duopoly market and an increase in ride-hailing car supply. This competitive effect could have tipped the scales, making an entire trip with a ride-hailing service more cost-effective and convenient than splitting a trip between a ride-share company and public transportation.

1. Introduction

In early 2017, New York's Metropolitan Transportation Authority announced that annual New York subway ridership fell in 2016 compared to 2015, the first annual dip since 2009. Although weekday subway ridership was at its highest level since 1948, the 3% dip in weekend ridership between 2015 and 2016 led to the net decline in subway use. The authority stated that several factors could have contributed to the decline: "rising subway delays, *the popularity of Uber and other apps*, and weekend maintenance work that disrupt[ed] service" (*emphasis ours*) (Fitzsimmons 2017).[1]

That private ride-hailing services like Uber and Lyft would be an appealing substitute for public transit is an intuitive notion, especially when public transit stops are several blocks away, buses or trains come infrequently, and public transit may be unsafe or unclean. At the touch of a button on a smartphone, a traveler can procure reliable, relatively private, and safe[2] door-to-door transit within minutes. Better yet, the price of the Uber or Lyft ride may only be $5 or $10 more than a less

[1] Curiously, a full year of low gasoline prices was not mentioned as a potential reason for more car-bound weekend trips.
[2] Whether using Uber and Lyft is actually safer than public transportation, especially for women, is an open question. For example, the website http://www.whosdrivingyou.org/rideshare-incidents catalogs passenger deaths, assaults, kidnappings, and endangerment at the hands of ride-hailing company drivers.

comfortable and less convenient bus or subway ride.[3,4] For example, Schwieterman and Michel (2016) compared the price and speed of fifty trips in the Chicago area. Each trip was started at the same time by two people but one person used UberPool, Uber's carpooling service where a passenger can expect to share their trip with one or two other people, and the other used Chicago's public transit system, either a bus or subway line. The average time for an UberPool trip was 35:52 minutes and the average time for the same trip on public transportation was 48:29 minutes. The average cost of the UberPool trip was $9.66 and the average cost of the public transit trip was $2.29.[5]

However, there is an alternative narrative that, rather than depressing public transit use, ride-hailing services *boost* (complement) public transit use, all else equal. In this narrative, Uber and Lyft are conveyances that lower public transportation's access and egress time. For example, Uber and Lyft increase the likelihood of using public transportation as the primary mode of transportation by solving the "last mile" problem (Wang and Odoni 2016). The "last mile" problem refers to the difficulty in getting people from a public transportation stop or station to their final destination, whether it is their home, work, a store, or entertainment. In fact, a report from Uber highlighted their product as a solution to the "last mile" problem by offering "residents of areas underserved by public transit a reliable and fast link to public transportation, effectively expanding the coverage of existing transit networks" (p. 27, Uber 2015).

As far as we can tell, there is no publicly available research on the ways that ride-hailing services substitute and complement public transportation use in major cities across the US.[6] For example, it appears the New York Metropolitan Transportation Authority's statement on the impact of ride-hailing companies on public transportation use in New York is speculative; the statement does not appear to be based on any rigorous data analysis.

Here we provide some information on the relationship between ride-hailing services and public transit use in major US urban areas. Our aim is to determine if public transportation and ride-hailing services are substitutes or complements for each other or if they have a more complex relationship. To do this we use a discontinuity regression design to measure the effect of private ride-hailing service entry on total public transportation use in the US' largest urban areas. We find that, on average, monthly public transportation use in urban areas increased immediately following the entry of the first private ride-hailing service. However, we find the entry of the second ride-hailing company, typically

[3] While researchers have collected snatches of data that Uber and Lyft charge for a ride, including surge prices, the companies do not provide comprehensive datasets on their prices. For example, Cohen et al. (2016) were provided a database of 50 million individual-level interactions with Uber's app. For each interaction the researchers are given the price the app users saw, but only in relative terms. The numeraire price was never reported.

[4] Whether Uber can continue to offer low prices is debatable. Based on private financial statements that Uber shared with investors and that were published in the financial press, Hubert Horan found that "Uber passengers were paying only 41% of the actual cost of their trips" from 2013 through the first half of 2015; Uber was subsidizing the rest. (http://www.nakedcapitalism.com/2016/11/can-uber-ever-deliver-part-one-understanding-ubers-bleak-operating-economics.html)

[5] Given these statistics a person who chooses UberPool over public transportation is willing to pay at least $7.37 on some combination of saving 12 minutes and 38 seconds on commute time in a cleaner, more private mode of transportation. This translates to $35.00 per hour. The US Department of Transportation reported that the average US consumer is willing to pay $24.00 to save an hour of commute time (https://cms.dot.gov/sites/dot.gov/files/docs/USDOT%20VOT%20Guidance%202014.pdf).

[6] See Kelley (2016) for analysis on the impact of ride-hailing services on taxi-cab use.

Lyft, several months later erased the spike in public transportation use seen immediately after first entry, all else equal. We repeat our analysis only using public transportation trips made by rail (e.g., light rail and commuter rail) and then again only using public transportation trips made by bus. While the incremental impact of first and second entry on rail use is similar to our overall results, there is some evidence that bus use and ride-hailing services remained complementary even after the entry of the second company. Overall, our analysis shows that public transportation use and ride-hailing services can be complementary initially, but the subsequent duopolistic competition between Uber and Lyft tends to reverse any preliminary complementarities.

2. Theory

Consider an individual who can either drive her own car (C), use public transportation (PT), or a hail a ride (RS) to get to her destination.[7] This individual *j* has preferences over consumption of a composite good, X_j, and a generalized transportation cost, T_j. We assume individual *j* has a quasilinear utility function of the form,

$$U_j = X_j - T(s_j(PT_j, RS_j), a_j(PT_j, RS_j), w_j(PT_j, RS_j), m) \tag{1}$$

where transportation cost is a function of transportation speed s_j (e.g., miles per hour), access and egress time a_j, waiting time w_j, and trip distance m (Anderson 2014). PT_j and RS_j are *j*'s transportation mode choice variables. Let $PT_j = 1$ if individual *j* chooses to travel to her destination by PT and equals 0 otherwise. Let $RS_j = 1$ if individual *j* chooses to travel to her destination with a hailed ride and equals 0 otherwise. PT_j and RS_j can both be equal to 0 (she uses her car to get to her destination) but they both cannot be equal to 1 (she cannot both use PT and a ride hailing service). In other words, we assume no multi-modal trips.[8]

Individual *j* maximizes her utility subject to her budget constraint,

$$Y_j = X_j + m\left[p_{PT} PT_j + \left(1 - PT_j\right)\left(p_{RS} RS_j + p_C \left(1 - RS_j\right)\right)\right] \tag{2}$$

where income Y_j must equal spending on the composite good X (whose price is normalized to unity) plus trip costs (Anderson 2014). Let p_{PT}, p_{RS}, and p_C measure the per distance unit of travel price when using PT, RS, and a car, respectively.

Let us convert $T(s_j(PT_j, RS_j), a_j(PT_j, RS_j), w_j(PT_j, RS_j), m)$ from (1) into a dollar value, just like X_j. Let *j* value time at v_i dollars per hour. Small and Verhoef (2007), Abrantes and Wardman (2011), and others have found that people place a higher value on time spent waiting for transit (in our case given by w), stuck in traffic, or walking (or more generally, egress time a) than they do on the same amount

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[7] In the theory section ride-hailing service includes taxis and cars driven by Uber and Lyft drivers.

[8] A "real-world" trip can use multiple modes. For example, *j* could drive her car from her home to a 'park and ride' lot and then take commuter rail to finish her trip or she could use a ride-share service to go from her home to a light rail station and use the light rail to finish her trip.

of time in other circumstances. Defining a "delay multiplier" $d > 1$, we can write the individual's (dis) value of time spent on a trip as,

$$v_j\left[PT_j\left(\frac{m}{s_{PT}}+d\left(a_{PTj}+w_{PT}\right)\right)+\left(1-PT_j\right)\left(RS_j\left(\frac{m}{s_{RS}}+d\left(a_{RSj}+w_{RSj}\right)\right)+\left(1-RS_j\right)\left(\frac{m}{s_C}+d\left(a_C+w_{Cj}\right)\right)\right)\right] \quad (3)$$

where all time variables are measured in hours. Now individual j's problem is to maximize

$$U_j = X_j - v_j\left[PT_j\left(\frac{m}{s_{PT}}+d\left(a_{PTj}+w_{PT}\right)\right)+\left(1-PT_j\right)\left(RS_j\left(\frac{m}{s_{RS}}+d\left(a_{RSj}+w_{RSj}\right)\right)+\left(1-RS_j\right)\left(\frac{m}{s_C}+d\left(a_C+w_{Cj}\right)\right)\right)\right] \quad (4)$$

subject to equation (2). In equations (3)-(4), access and egress time is assumed to be the same for all individuals who use a car for their trip (there is no j subscript with a_C). However, access and egress time for PT and ride hailing service is specific to j (a_{PTj} and a_{RSj}) given differences in bus or train stop proximity across the urban landscape and unequal spatial concentrations of ride hailing suppliers (e.g., there are many Uber drivers in Manhattan and Brooklyn but not as many on Long Island). Further, in equations (3)-(4) waiting time at a PT stop is not specific to a person but to the transportation system in the city, thus no j subscript on w_{PT}. However, driving delay time (i.e., the difference between driving time in free-flow traffic and actual driving time) is specific to the location of j's trip within a city, thus w_{RS} and w_C in (4) include the subscript j (e.g., some places in a city are less congested than others).

Assume that $PT_j = 1$ maximizes j's utility subject to her budget constraint. For this to be the case, both of the following two inequalities must hold for individual j,

$$\underbrace{\frac{m\left(p_{RS}-p_{PT}\right)}{v_j}}_{\text{Benefit of PT relative to RS}} \geq \underbrace{\frac{m}{s_{PT}}-\frac{m}{s_{RS}}}_{\text{Travel time cost of PT relative to RS}} + \underbrace{d\left(a_{PTj}-a_{RSj}+w_{PT}-w_{RSj}\right)}_{\text{Delay time cost of PT relative to RS}} \quad (5)$$

$$\underbrace{\frac{m\left(P_C-P_{PT}\right)}{v_j}}_{\text{Benefit of PT relative to C}} \geq \underbrace{\frac{m}{s_{PT}}-\frac{m}{s_C}}_{\text{Travel time cost of PT relative to C}} + \underbrace{d\left(a_{PTj}-a_C+w_{PT}-w_{Cj}\right)}_{\text{Delay time cost of PT relative to C}} \quad (6)$$

The left-hand terms of (5) and (6), $\frac{m\left(P_{RS}-P_{PT}\right)}{v_j}$ and $\frac{m\left(P_C-P_{PT}\right)}{v_j}$, measure j's additional cost from using a ride-hailing service or her own car, respectively, instead of PT (division by v_j means that the additional cost is measured in hours instead of dollars). We can also interpret this as the benefit of using PT in lieu of the other options (an avoided cost). The right-hand terms of (5) and (6) measure the additional "effective" hours of transportation time j incurs from choosing to use PT over each of the other two modes of transportation. Therefore, as long as the avoided cost of using PT in lieu of the other two modes (the left-hand side of equations (5) and (6)) is greater than the additional "effective" hours of transportation time *j* incurs by using PT instead of the other modes (the cost of PT use), then *j* will choose PT.

If we re-arrange (5) and (6) such that the terms that vary across individuals fall on the left-hand side of the inequalities we have,

$$d\left(a_{PTj} - a_{RSj} - w_{RSj}\right) - \frac{m\left(p_{RS} - p_{PT}\right)}{v_j} \leq \frac{m}{s_{RS}} - \frac{m}{s_{PT}} - dw_{PT} \tag{7}$$

$$d\left(a_{PTj} - w_{Cj}\right) - \frac{m\left(p_{C} - p_{PT}\right)}{v_j} \leq \frac{m}{s_{C}} - \frac{m}{s_{PT}} - d(w_{PT} - a_C) \tag{8}$$

At any point in time, those individuals *j* with lower opportunity cost of time (low *v*), low access and egress time to PT (low a_{PT}), relatively high access and egress time to RS (high a_{RS}), and needing to make a trip across a congested area of the city (high w_C and w_{RS}) are the most likely to choose PT for their trip, all else equal.

Changes in transportation prices, transportation infrastructure, and transportation options will also change the likelihood of PT use for a trip by *j* at any point in time. Generally, as the monetary and time costs of using PT falls for *j* relative to the other two modes, the more likely she is to use PT for her trips. Specifically, if the ratios p_{PT} / p_C, P_{FT} / P_{RS}, a_{PTj} / a_{RSj}, a_{PTj} / a_C, or w_{PTj} / w_j decrease then individual *j*'s likelihood of using PT for any given trip increases.

In this paper we estimate the impact that the entrance of the ride hailing service companies, Uber and Lyft, have had on PT use across the US's largest cities. Entrance of ride-hailing service companies will affect the terms in equations (6) and (7) in several ways. First, their entrance has lowered a_{RS} for many people across US cities. For example, Rayle et al. (2014) found that in San Francisco wait times for UberX cars were shorter than those for taxis. [9] Further, the entrance of Uber and Lyft has led to improvements in taxi service in several cities (Wallsten 2015). Second, in most cities Uber and Lyft have charged less per unit distance travelled than taxis (Silverstein 2014), although there are exceptions (e.g., Salnikov et al. 2015). Therefore, the advent of Uber and Lyft has tended to lower average p_{RS} for many people across the US.[10,11] All else equal, decreases in a_{RS} and p_{RS} in an urban area's ride hailing market should make individuals less likely to use PT for any given trip, thereby reducing overall PT use in the urban area.

Just as the entry of Uber and Lyft has incentivized taxicab companies to improve their service, we suspect that intense competition between Uber and Lyft has lowered a_{RS} and P_{RS} even more over time in most major US cities. Up to this point in time Uber and Lyft have tended to stagger their entry

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[9] Uber has several different types of services. UberX is Uber's low cost service.
[10] During Uber's infamous surge pricing periods, average P_{RS} will have increased.
[11] There is some evidence that Uber and Lyft are becoming consistently cheaper than taxis in many US cities. For example see http://www.cnbc.com/2015/08/31/whats-cheaper-in-your-city-cabs-or-ride-shares.html.

into cities, where, at least in the bigger US cities, Uber has almost always been the leader and Lyft the follower (Figure 1). We would not be surprised to find that the second entrant and the accompanying advertising and promotion campaigns and driver recruitment has spurred even greater reductions in a_{RS} and P_{RS}, thereby further reducing overall PT use in cities.

In our theoretical model, it is clear that advent of Uber and Lyft will reduce PT use; that Uber and Lyft are substitutes for PT use. However, what if we relaxed the constraint on multi-modal trips in our model? In this more expansive interpretation of behavior, Uber and Lyft are conveyances that lower PT's access and egress time (an input to PT use), and the ride-hailing services can now become complements to PT use. Specifically, Uber and Lyft can make using PT as the primary mode of a trip more likely, all else equal, by lowering PT egress time (lowering a_{PT}).[12] If this ride hailing and PT use complementarity effect is strong enough then it is possible that the entry of Uber and Lyft has actually increased PT use despite the decreases in a_{RS} and p_{RS} (and the small increase in p_{PT} use as we have to add the price of using Uber or Lyft for a "one mile" trip to a subway or bus stop).

Our simple model and the one mode constraint masks another way that enhanced ride-hailing services and PT use can be complementary: Uber has claimed that its presence in a city makes it more convenient for individuals to use a combination of PT and Uber in lieu of their car for trips. For example, Uber has pointed out that in Chicago, because "riders can always be confident of a ride back, Uber also removes the worry over whether transit services will be reliable or operating late at night, encouraging more people to use Chicago Transit Authority trains and buses, Metra commuter rail, and other public transit when they head out for a night on the town" (p. 27, Uber 2015). Again, if all of these ride hailing and PT complementarity effects are strong enough, it could be that the entry of Uber and Lyft has increased PT use despite the decreases in a_{RS} and P_{RS}.

3. Data and Empirical Framework

We use PT ridership data from the largest US urban areas with a discontinuity regression model design to test whether the entry of Uber and Lyft, typically staggered by several months, has been associated with an increase or decrease in PT use. Our regression model includes proxies for most of the factors that affect mode choice as given in equations (5)-(8). *Ex ante* we expect to find that the entry of these services has decreased PT ridership because of entry's downward pressure on a_{RS} and P_{RS}.

3.1. Data

Monthly PT ridership data at the urbanized area (UZA) level is provided by the Federal Transit Authority (FTA) (https://www.transit.dot.gov/ntd/ntd-data). The FTA measures PT usage with monthly "unlinked passenger trips" (UPTs). UPT, given by UPT_{um} where u indexes UZA and m months, measures

[12] In fact some local governments have subsidized Uber to solve the last mile problem, meaning P_{PT} will not increase for the user. For example, "Pinellas County in the Tampa Bay area just started a pilot program that pays up to $3 per trip to riders who take Ubers or taxis to bus stops." Other public transportation systems have made the last mile problem easier to solve by coordinating their systems' and Uber's apps. (http://wastefraudandabuse.org/regulating-uber-subsidizing/)

the number of passenger trips across all of u's PT vehicles in month m.[13] Unlinked means that every boarding increases UPT by one even if one person-trip is responsible for multiple boardings. For example, if a person rides a bus and then immediately transfers to the subway to complete her trip then UPT_{um} count has increased by two, not one.[14] Over the course of the year, UPT in a UZA can swing dramatically. Typically, UPT is lowest in the winter months and greatest in the spring and fall. These seasonal gyrations can be seen in Figure 2, where we graph monthly UPT for the four largest US UZAs. The graphs also indicate the month that Uber and Lyft entered the respective market.

In the theoretical model, prices for each mode are measured per unit distance. The price data we use in this analysis is a bit different. First, p_{PTum} measures price per UPT in UZA u in month m. Ideally, we would calculate p_{PTum} by dividing UZA u's fare revenue in month m by u's UPT in month m. Unfortunately, fare revenue is only reported by the FTA on an annual basis. Therefore, we divide u's annual fare revenue (Figure 3) by u's annual UPT and set p_{PTum} equal to this number for each month m in that calendar year.[15] Second, p_{Cum}, theoretically the per mile cost of using a car, is measured here with the real average price of a gallon of gas in UZA u in month m. When possible, we used monthly gas price data specific to the metropolitan statistical area in which the UZA is located[16], otherwise we use the UZA's state or region price datasets.[17] Finally, we do not have data on p_{RSum}. However, we do know the month that Uber and Lyft entered each UZA u.[18] We assume each successive entry places sustained downward pressure on p_{RSum}. According to equations (5)-(8), an increase in p_{PTum} / p_{Cum} makes PT use less likely. Therefore, we expect to find that UPT_{um} decreases in p_{PTum} but increases in p_{Cum}, all else equal.

We do not have the data to measure PT egress (a_{PTum}) directly. However, we believe the variable per capita mileage of PT in u in month m, given by $Mile_{um}$, is an indirect measure of a_{PTum}. We surmise that as $Mile_{um}$ increases, more and more citizens of u will have better access to the system and a_{PTum} decreases for more and more people. According to equations (5)-(8), an increase in a_{PTum} makes PT use more likely. Therefore, all else equal, we expect to find that UPT_{um} increases in $Mile_{um}$. We calculated $Mile_{um}$ by dividing a UZA u's sum of year t's rail and non-rail public transposition miles (as

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[13] The FTA mandates that agencies submit a 100% count of UPTs, yet some agencies do not have the technology to meet this requirement. In this case, they are exempt and may report based on a sample, but the FTA does not keep track of the methods used by each agency. Due to this limitation, the UPTs may not be accurate when the sampling method is used.

[14] We include almost all modes of public transportation in UPT_{um}. The one exception is "Ferry Boat." The different modes reported to the FTA are outlined in Supplementary Information Table A.

[15] p_{PTum} does not measure the amount a person pays to use public transportation as many commuters spread their public transportation "entry fee" over multiple trips.

[16] See the US Bureau of Labor Statistics' website https://www.bls.gov/regions/midwest/data/averageenergyprices_selectedareas_table.htm for specific metropolitan area gasoline prices. The BLS has metropolitan level data for Atlanta, Boston, Chicago, Cleveland, Dallas, Detroit, Houston, Miami, Los Angeles, New York, Philadelphia, San Francisco, Seattle, and Washington, D.C.

[17] See the US Energy Information Administration's website http://www.eia.gov/dnav/pet/pet_pri_gnd_a_epmr_pte_dpgal_m.htm for state and regional level monthly gasoline prices.

[18] See appendix for sources.

reported to the FTA) by the UZA u's population in year t[19] and then assigning the annul number to each month in year t.[20]

We do not have data proxies for wait time by mode choice (w_{PT}, w_{RS}, and w_C). However, our UZA dummies will control for the relative degree of congestion on the roads (w_{RS} and w_C) and the frequency of buses and trains (w_{PT}) across UZAs. Our UZA dummies also control for the extent and scope of taxi cab service, the original but less convenient and flexible ride-hailing service, in a city. The continued tight regulation of the taxi industry across US cities, including limits on entry and fare ceilings (Teal and Berglund 1987, Cairns and Liston-Heyes 1996), means the service has remained rather static over the years in US cities and thus treating it as a fixed effect unique to each city is proper (e.g., the taxi industry is regulated differently in New York City than Minneapolis). We also include seasonal dummies to control for a UZA's seasonal variation in PT use. The seasonal dummies control for the impact that weather can have on modal egress, access, and wait times and overall demand for trips (Stover and McCormack 2012). We also include UZA's monthly unemployment rates in the regression model, given by $unemp_{um}$. Monthly unemployment rates control for the impact of general economic conditions and the price sensitivity of a city's populous on overall demand for trips (Buehler and Pucher 2012). Monthly unemployment data for each UZA comes from the unadjusted Local Area Unemployment Statistics (LAUS) series at the Bureau of Labor Statistics.[21]

The UZAs we use are mostly drawn from the list of the US' top 30 MSAs as measured by 2010 population, but there are a few exceptions. Cities where Uber or Lyft entered after July 2014 were removed to ensure that all cities had at least two years of accurate UPT counts post-second entry. This meant dropping data from Washington, DC, Philadelphia, and Honolulu from our dataset. Moreover, San Francisco and Oakland share a UZA. Therefore, UPT counts for each city cannot be separated (and we cannot treat the UZA as one entity in our empirical model because each ride-hailing company entered these two cities at different times). So we drop the San Francisco-Oakland UZA from our database. In the end we have a database with 28 cities. See SI Table Y for the list of cities in our database and the dates of Uber and Lyft entry.

3.2 Regression Discontinuity Design

The simplest sharp regression discontinuity (RD) design we use is,

$$UPT_{um} = \alpha + \rho_F F_{um} + \rho_S S_{um} + \gamma_1(m_{Fu} - m_{F0u}) + \theta_1(m_{Su} - m_{S0u}) + \beta\mathbf{X}_{um} + e_{um} \qquad (9)$$

where m indicates months, m_{F0u} is the month that the <u>first</u> ride-share company entered UZA u, m_{S0u} is the month that the <u>second</u> ride-share company entered UZA u, and

[19] Annual population data by UZA comes from the American Community Survey. We used ACS 1-year estimates. https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml

[20] In some cases, a UZA did not report mileage in a given year. If mileage was unreported for year t we estimated it by averaging the mileage in prior and subsequent years (t – 1 and t + 1 years, respectively).

[21] BLS data is reported at the core-based statistical area (CBSA) level. UZA and CBSA do not align perfectly. The Los Angeles-Long Beach-Anaheim, CA UZA was the most incongruent, with only 95% of the 2010 census population of the UZA inside the relevant CBSA. Given that the economic health of a city shouldn't differ drastically across a CBSA border, the cities with UZAs that extend past the CBSA area are still be included in the model but are similar enough so that we do not have to worry about the spatial misalignment.

$$F_{um} = \begin{cases} 1, \text{if } m_{Fu} \geq m_{F0u} \\ 0, \text{if } m_{Fu} < m_{F0u} \end{cases} \tag{10}$$

$$S_{um} = \begin{cases} 1, \text{if } m_{Su} \geq m_{S0u} \\ 0, \text{if } m_{Su} < m_{S0u} \end{cases} \tag{11}$$

For example, suppose Uber entered UZA *u* in May of 2012. In this case, $m_{Fu} - m_{F0u} = 0$ and $F_{um} = 1$ for *m* = May, 2012, $m_{Fu} - m_{F0u} = 1$ and $F_{um} = 1$ for *m* = June, 2012, etc. In the opposite direction, $m_{Fu} - m_{F0u} = -1$ and $F_{um} = 0$ for *m* = April, 2012, $m_{Fu} - m_{F0u} = -2$ and $F_{um} = 0$ for *m* = March, 2012, etc. The terms $m_{Su} - m_{S0u}$ and S_{um} are evaluated in the same manner but based on the month the second ride-share company enters.[22] Further, in the simplest sharp regression discontinuity design $\mathbf{X}_{um}$ includes UZA and seasonal dummies and monthly unadjusted unemployment rates. The coefficients ρ_F and ρ_S indicate the effect of the first and second entrants, respectively, on PT use in the representative UZA while $\rho_F + \rho_S$ indicates the joint effect of both entries. The coefficients γ and θ measure the impact of the change in running time, pre- and post-treatment, on PT usage.

We also estimate a RD model with more functional flexibility and a wider set of variables in $\mathbf{X}_{um}$,

$$\begin{aligned} UPT_{um} = {} & \alpha + \rho_F F_{um} + \rho_S S_{um} + \gamma_1(m_{Fu} - m_{F0u}) + \underbrace{\gamma_2(m_{Fu} - m_{F0u})^2}_{\text{new to (12)}} + \theta_1(m_{Su} - m_{S0u}) + \\ & \underbrace{\theta_2(m_{Su} - m_{S0u})^2}_{\text{new to (12)}} + \underbrace{F_{um}[\delta_1(m_{Fu} - m_{F0u}) + \delta_2(m_{Fu} - m_{F0u})^2]}_{\text{new to (12)}} + \\ & \underbrace{S_{um}[\mu_1(m_{Su} - m_{S0u}) + \mu_2(m_{Su} - m_{S0u})^2]}_{\text{new to (12)}} + \beta\mathbf{X}_{um} + e_{um} \end{aligned} \tag{12}$$

The addition of the terms $(m_{Fu} - m_{F0u})^2$ and $(m_{Su} - m_{S0u})^2$ means that change in running time, pre- and post- treatment, can have a non-linear impact on UPT_{um}. Further, multiplying change in running time and its square by the treatment effects means that running time can have a different impact on UPT_{um} before treatment than after treatment. For example, entry of a ride-hailing service in a UZA may initially have little impact on transportation choices in the UZA due to consumer unfamiliarity with these services and a limited supply of drivers. Only after several months of advertising and outreach will people seriously begin considering the ride-hailing service as a viable transportation alternative. Further, only after several months of operation will there be enough drivers to support rising demand for these services.

Therefore, in the expanded model (12) the term,

$$\rho_F + \delta_1(m_{Fu} - m_{F0u}) + \delta_2(m_{Fu} - m_{F0u})^2 \tag{13}$$

[22] In Pittsburgh Lyft entered prior to Uber. In all other UZAs we study Uber entered first or they entered simultaneously. The companies entered simultaneously in Austin, Charlotte, Houston, and Nashville.

indicates the effect of the first entrant on PT use with ρ_F expressing the instantaneous size of the discontinuity and δ_1 and δ_2 revealing the momentum effects of the first entrant on PT. Further, in the expanded model (12) the term,

$$\rho_S + \mu_1(m_{Su} - m_{S0u}) + \mu_2(m_{Su} - m_{S0u})^2 \tag{14}$$

indicates the effect of the second entrant on PT use in model (12) with ρ_S expressing the size of the discontinuity at the cut-off and μ_1 and μ_2 revealing the momentum effects of the second entrant on PT. Further, the joint effect of both entries in the expanded model is given by the sum of (13) and (14). Finally, the variables in $\mathbf{X}_{um}$ now include p_{PTum} , p_{Cum}, and $Mile_{um}$ as well as those variables in model (9)'s version of $\mathbf{X}_{um}$.

We use an RD bandwidth of 36 months centered on the timing of the first entrant (all UZAs had the second rise-share company enter within 36 months of the first). In some cases a UZA in our dataset may not have 36 months of post-first entry data but all UZAs have 36 months of pre-first entry data. The shortage of post-first entry observations is more pronounced in the estimate of model (M2). PT mileage has not been reported for 2015 and 2016 and fare revenue data has not been reported for 2016. In contrast, the data used to estimate model (9) are through October, 2016.

4. Results

The estimates of models (9) and (12) when UPT_{um} is measured in 10,000s of monthly passenger trips across all PT vehicles are given in Table 1. In both estimates, the first ride-hailing company entrant causes an instantaneous jump in monthly PT use, all else equal. Specifically, an additional 1,249,100 monthly rides in the estimate of model (9) (i.e., $\hat{\rho}_F = 124.91$ is significant at a p = 0.01 level) and an additional 1,092,600 monthly rides in the estimate of model (12) ($\hat{\rho}_F = 109.26$ is significant at a p = 0.1 level). In model (12), the impact of time on UPT_{um} 1) can be different prior to and after ride-hailing company entry and 2) is assumed to be non-linear. In the estimate of this more elaborate model, UPT_{um} accelerates over time after first entry, albeit in a statistically insignificant manner (i.e., the first and second derivatives of $\delta_1(m_{Fu} - m_{F0u}) + \delta_2(m_{Fu} - m_{F0u})^2$ with respect to m_{Fu} are positive).

Conversely, the second entrant causes an instantaneous decrease in PT use, all else equal. Specifically, 1,601,100 monthly rides in the estimate of model (9) ($\hat{\rho}_S = -160.11$ is significant at a p = 0.01 level) and 92,850 monthly rides in the estimate of model (12) ($\hat{\rho}_S = -95.58$). While $\hat{\rho}_S$ itself is not statistically significant, the total effect of second entry, given by equation (14), is negative *and* statistically significant at the p = 0.01 levels when $m_{Su} - m_{S0u}$ equals 12, 24, and 36. In other words, the second entry progressively dampens UPT_{um}, all else equal, as time progresses. Therefore, on average, the second entrant mitigated the positive or complementary impact the first entrant had on PT use across the 30 largest US UZAs.

To determine if the second entrant completely reversed the gains in PT use associated with the advent of the first entrant we estimate the *joint* impact of Uber and Lyft entry on UPT_{um}. Specifically, $\hat{\rho}_F + \hat{\rho}_S < 0$ from model (9) and,

$$\begin{aligned} &\hat{\rho}_F + \hat{\delta}_1(m_{Fu} - m_{F0u}) + \hat{\delta}_2(m_{Fu} - m_{F0u})^2 + \hat{\rho}_S \\ &\qquad + \hat{\mu}_1(m_{Su} - m_{S0u}) + \hat{\mu}_2(m_{Su} - m_{S0u})^2 < 0 \end{aligned} \tag{15}$$

from model (12) for the relative time combinations of,

$$m_{Fu} - m_{F0u} = 12 \text{ and } m_{Su} - m_{S0u} = 0 \tag{16}$$
$$m_{Fu} - m_{F0u} = 24 \text{ and } m_{Su} - m_{S0u} = 12 \tag{17}$$
$$m_{Fu} - m_{F0u} = 36 \text{ and } m_{Su} - m_{S0u} = 24 \tag{18}$$

indicates that the second entrant more than counters the positive impact the first entrant had on PT use; in fact, the negative impact of the second entrant on subsequent PT use overwhelms the positive impact of the first entrant on PT use. Furthermore, the joint impact of entry on PT use becomes increasingly negative over time (although none of these joint impact variables are statistically significant).

What story do the estimates of models (9) and (12) tell, at least across the US's largest UZAs? First, the positive impact of first entry on UPT in estimates of both models (i.e., $\hat{\rho}_F > 0$) suggests that customers generally treated first entrants as conveyances that lowed PT's access and egress time. In other words, initial ride-share company entry complemented PT usage). It could be that ride-hailing use after first entry was driven by two types of passengers: 1) people who would have otherwise taken their personal car on a trip now took the trip by Uber (or Lyft in the one case where it was first) and 2) people who used Uber to get to PT stops and had previously not done so due to the "last mile problem" or a late night trip segment.[23] In other words, first entry decreased a_{PTum} enough that a significant number of people chose PT as their primary (or at least co-equal) mode of trip transportation. However, the second entrant appears to have eliminated this trend. While a_{PTum} likely falls even more with the second entrant, we suspect that the competition between Uber and Lyft drove the price of ride-hailing (p_{RSum}) and ride-hailing egress (a_{RSum}) low enough so that more and more people choose to take their entire trip with a ride-hailing company instead of using ride-hailing as a convenient access to PT.

Our first set of results does not distinguish UPT by PT mode. However, UPT_{um} can be broken down by transportation mode (Table 2). Therefore, we re-estimate models (9) and (12) using bus UPT only[24] and then again using rail UPT only.[25] In each variation on the original model we construct p_{PTum} and $Mile_{um}$ variables that only include the relevant PT modes. Given,

- that the type of people who have access to and use light rail – commuter rail tend to be socioeconomically different than the people who have access to and use busses (Garrett and Taylor 1999, Hess 2012, Walker 2014),

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[23] In addition, some UZAs are using Uber and Lyft to provide paratransit. See "Boston MBTA Teams Up With Uber, Lyft Paratransit Pilot" http://www.metro.us/boston/mbta-teams-up-with-uber-lyft-for-paratransit-pilot-to-make-transportation-more-accessible/zsJpip---N44dzCbCPRls6/ and "Uber Now Offers Assitance for Elderly and Disabled" http://lifehacker.com/uber-now-offers-assistance-for-elderly-and-disabled-peo-1718398360. However, the number of paratransit UPTs in UPT_{um} are too small to make a statistical difference in our model.
[24] Transportation category modes CB, MB, RB, and TB in Supplementary Information Table A.
[25] Transportation category modes CR, HR, LR, MG, MO, SR and YR in Supplementary Information Table A.

- that people perceive qualitative differences between PT trips completed by rail versus bus (Ben-Akiva and Morikawa 2002, Cantwell et al. 2009, Scherer 2010, Scherer and Dziekan 2012); and
- that these modes are often marketed differently (Garrett and Taylor 1999, Scherer 2010)

we would not be surprised to find that the impact of ride hailing company entry on PT use will differ by mode.

The estimate of model (9) when UPT_{um} only includes rail passenger trips is similar to the estimate of model (9) when UPT_{um} includes all modes; compare columns (1) in Tables 1 and 3. The first entrant is associated with an immediate increase in rail UPT, all else equal, and the second entrant is associated with an immediate decrease in rail UPT, all else equal. Further, the joint impact of ride-hailing entry on rail UPT is net negative. The estimate of (12) with rail-only UPT also looks similar to the estimate of (12) with total UPT. Compare columns (2) in Tables 1 and 3.

However, the estimate of model (9) when UPT_{um} only includes bus passenger trips is *dissimilar* to the estimate of model (9) when UPT_{um} is made up of all modes; compare column (1) in Table 1 to column (3) in Table 3. In the bus-only UPT case, the first and second entrant are both associated with a boost in subsequent bus use and the joint effect ($\hat{\rho}_F + \hat{\rho}_S > 0$) is significant at a p = 0.05 level. However, the estimate of model (12) with bus-only UPT is fairly similar to the estimate of (12) with total UPT; compare column (2) in Table 1 to column (4) in Table 3. All in all, it appears that the decreases in ride-hailing price (p_{RSum}) and egress (a_{RSum}) due to ride-hailing company competition had a more negative impact on rail trip use than it did on bus trip use.

5. Robustness Checks

Our identification of the impacts of ride-hailing company entry on PT use could be biased if the order of company entry into cities was determined by public transportation considerations. For example, if Uber and Lyft targeted cities with the largest PT networks for entry first and then moved onto cities with smaller networks then the pattern of entry would not necessarily be exogenous to its impact on PT use.

To that end we plot order of entry into a UZA (by the first entrant only) against UZA population in the year of entry, annual UZA PT trips in the year prior to entry, UZA PT mileage in the year of entry, annual UZA PT trips per capita in the year prior to entry, and UZA PT mileage per capita in the year of entry (Figure 4). First we see that the New York UZA, one of the first UZAs that Uber entered, is so much larger in every dimension than the other UZAs. If we ignore the New York UZA no obvious pattern between order of entry and PT variables. For example, it does not appear that a linear line with a negative or positive slope would provide a good fit for any of the plots in Figure 4. In other words, other than the obvious decision to enter America's premier city first, there is not obvious evidence that Uber and Lyft targeted UZA entry order according to the size of PT networks.

6. Conclusion

The results of our analysis indicate that the entrance of the first ride-hailing company served as a complement to public transportation use, at least across the UZAs included in our database. However, after the entry of the second ride-hailing company, public transportation usage decreased in our studied UZAs to levels either at or below those recorded prior to first entry. Therefore, the joint presence of the two major private ride-hailing services transformed ride-hailing services from a public transportation complement to a public transportation substitute, at least in the studied UZAs. In addition, we found that this substitution effect strengthened over time. While our model does not explain why joint presence transformed ride-hailing from a complementary to a substitute good for public transportation, we offer some educated guesses for the switch. First, we speculate that after both ride-hailing companies entered the market, competition for market-share led both companies to reduce prices to the point that many people in the studied UZAs were incentivized to use the ride-hailing services exclusively in lieu of public transportation. Second, we speculate that using ride-hailing services in lieu of public transportation became easier and more convenient over time as Uber and Lyft built up their stock of drivers in the studies UZAs, thereby reducing ride-hailing service wait and egress time.

While we cannot prove that price competition caused ride-hailing services and public transportation to become substitute we do have evidence that Uber and Lyft regularly engage in price competition to win market share. For example, in January 2014, Uber announced it was both introducing UberX, their most affordable service, into more cities and cutting prices of the existing UberX service in other cities.[26] In January 2015, Uber made another announcement that they would be dropping prices again in 48 cities around the US as part of a "Beating the Winter Slump" campaign to encourage ridership.[27] In January 2016, Uber indicated that they would be cutting prices a third time in 100 cities around the US and Canada. Los Angeles and San Francisco saw fares cut by 10%, while other cities such as Houston and Richmond, Virginia saw even larger decreases.[28] Lyft has also been aggressive about cutting prices. For example, in 2016 Lyft dropped fares in 48 cities. [29,30] Lyft has continued to lower prices in 2017 while Uber hasn't. Specifically, in January, 2017, Lyft lowered prices in 42 cities around the US.[31] Lyft may have felt compelled to unilaterally lower prices given Uber's continued market share dominance over Lyft. For example, in 2016 Lyft generated 163 million trips across the US while Uber generated 78 million trips across the US in December, 2016 alone. All in all, this evidence of price competition between Uber and Lyft supports our speculative notion that duopolistic competition between the two companies has helped convert ride-hailing service from a public transportation complement to a public transportation substitute.

Our results also suggest that ride-hailing service entry affected the behavior of bus riders differently than it did rail riders. In some cities there is no rail public transportation option. However, for the cities that have both modes, the difference in usage response to ride-hailing entry is a topic worth exploring further. In our model estimates, ride-hailing services never became a substitute for bus use. If anything, the two transportation types displayed a complementary relationship. One theory: the typical bus rider is poorer than the typical rail rider and ride-hailing prices are still much

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[26] https://newsroom.uber.com/situation/

[27] https://newsroom.uber.com/beating-the-winter-slump-price-cuts-for-riders-with-guaranteed-earnings-for-drivers/).

[28] https://newsroom.uber.com/beating-the-winter-slump-price-cuts-for-riders-and-guaranteed-earnings-for-drivers; https://www.bloomberg.com/news/articles/2016-01-09/uber-drops-prices-in-80-cities-in-the-u-s-and-canada

[29] https://www.forbes.com/sites/briansolomon/2016/01/25/is-uber-trying-to-kill-lyft-with-a-price-war/#14024afb6573 ; https://blog.lyft.com/posts/start-off-2016-with-lower-prices

[30] http://ridesharedashboard.com/2017/01/24/lyft-adjusts-winter-pricing-78-cities/

[31] http://ridesharedashboard.com/2017/01/24/lyft-adjusts-winter-pricing-78-cities

higher than the typical bus rider's reservation price for ride-hailing services. Conversely, for richer rail users, their reservation price for ride-hailing services is much higher. Thus, price competition among Uber and Lyft make it much more likely that the typical rail user will use a ride-hailing service than a typical bus user. Further, rail public transportation fares are generally higher than fares for bus public transportation. For example, in our database the average fare per rail UPT is $1.36 and the average fare per bus UPT is $0.88. For many rail users the difference in rail fare and the ride-hailing fares, driven low by oligopoly competition, could be low enough to entice a substitution to ride-hailing services. However, for bus users the difference in bus fare and the ride-hailing fares may be still too large to justify a substitution towards ride-hailing use.

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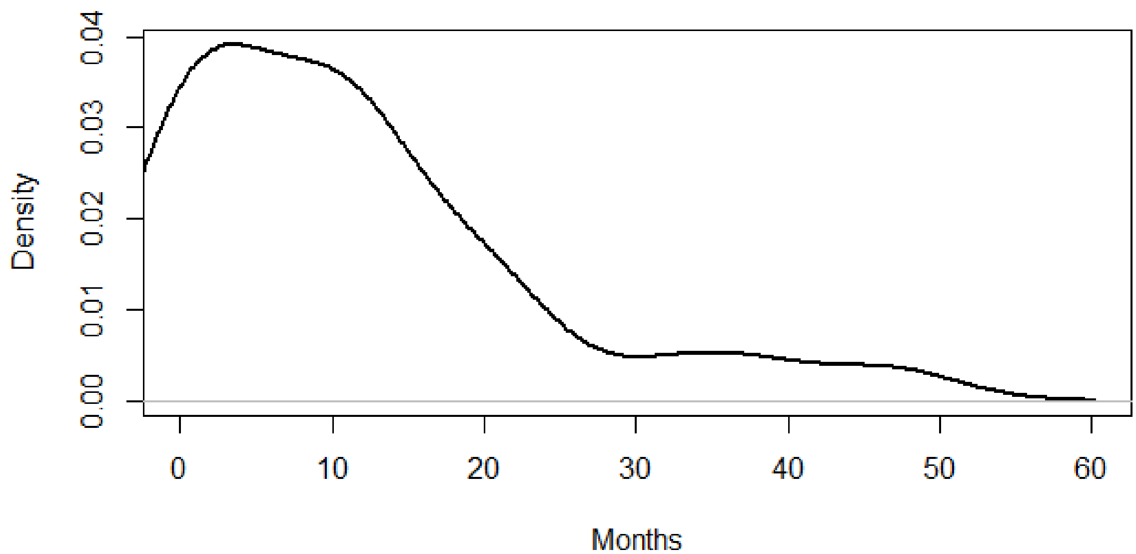

Figure 1: Density of months between first and second ride-hailing company entry across 28 major US UZAs. See SI Table B for data used in this density.

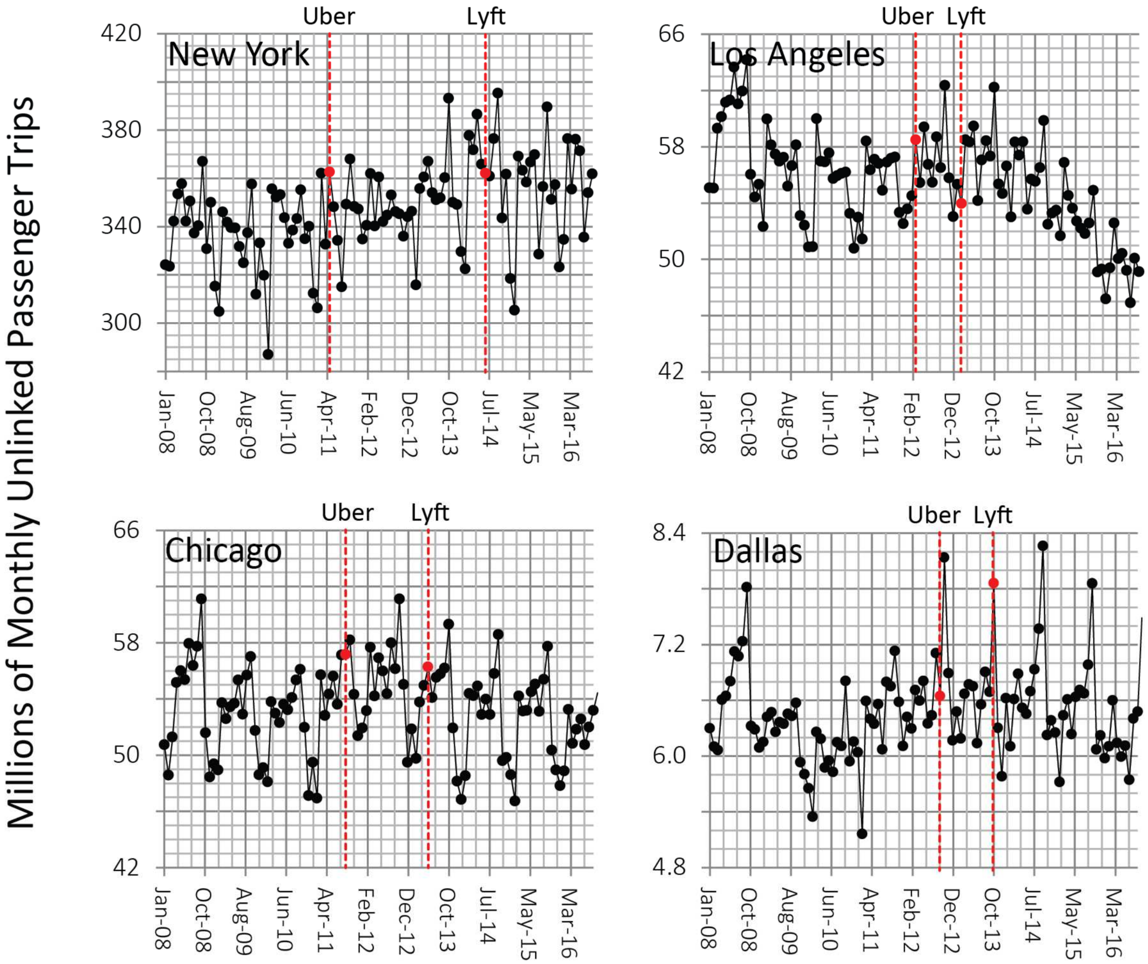

Figure 2: Monthly Unlinked Passenger Trips (UPTs) in the four largest US Urbanized Areas (UZAs) and the Dates of Uber and Lyft Entry into the Ride Hailing Market (indicated by red dot and red dotted line). The official names of the UZAs are New York-Newark, NY-NJ-CT; Los Angeles-Long Beach-Anaheim, CA; Chicago, IL-IN; and Dallas-Fort Worth-Arlington, TX.

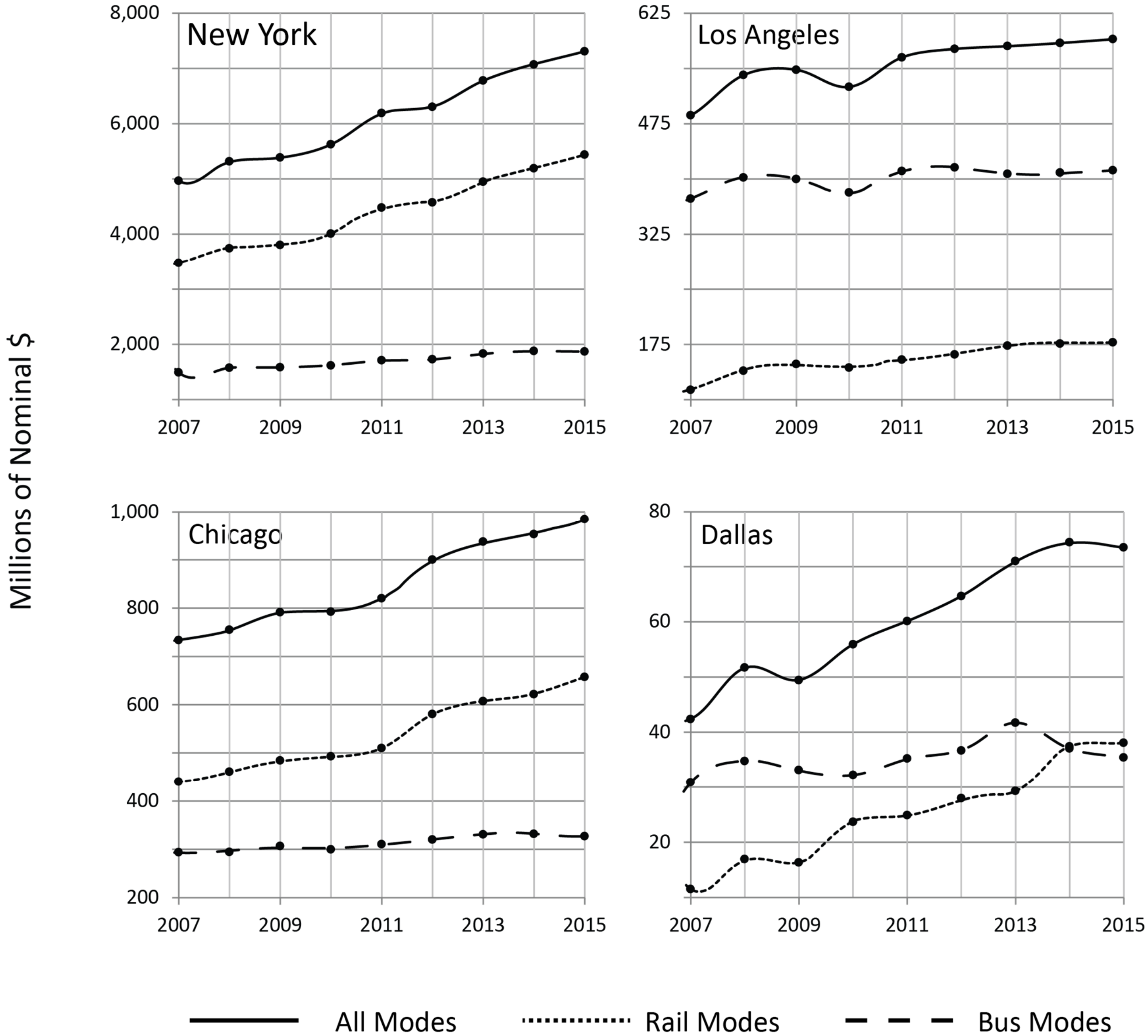

Figure 3: Annual public transportation fare revenue in the four largest US Urbanized Areas (UZAs). All dollars are nominal. The official names of the UZAs are New York-Newark, NY-NJ-CT; Los Angeles-Long Beach-Anaheim, CA; Chicago, IL-IN; and Dallas-Fort Worth-Arlington, TX.

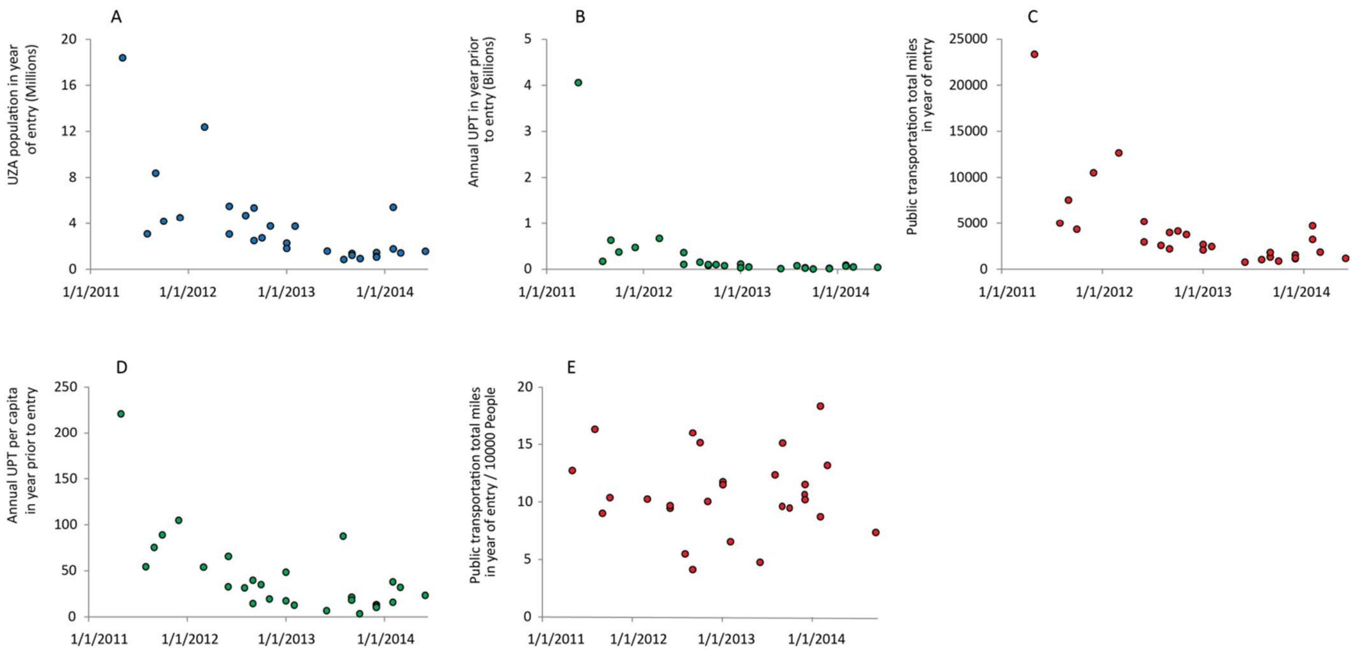

Figure 4: Order of ride-hailing private company entry into a UZA (in ascending order on the x-axis) against (A) UZA population in year of entry, (B) annual UZA UPT in year prior to entry, (C) UZA PT total miles in year of entry, (D) annual UZA UPT per capita in year prior to entry, and (E) UZA PT total miles in year of entry per 10,000 people.

Table 1: Explaining total monthly unlinked passenger trips in an urbanized area

Model Specification	(1)	(2)
First entrant treatment (ρ_F)	124.91***	109.26*
	(36.52)	(58.58)
First entrant treatment - 12 months since entry		27.24
		(129.98)
First entrant treatment - 24 months since entry		136.18
		(259.59)
First entrant treatment - 36 months since entry		436.10
		(442.00)
Second entrant treatment (ρ_S)	-160.11***	-92.85
	(35.12)	(62.68)
Second entrant treatment - 12 months since entry		-324.64***
		(93.68)
Second entrant treatment - 24 months since entry		-945.95***
		(284.41)
Second entrant treatment - 36 months since entry		-1956.8***
		(751.99)
Total Treatment ($\rho_F + \rho_S$)	-35.20	
	(41.73)	
Total treatment - 12 months since first entry, 0 months since second entry		-65.62
		(132.02)
Total treatment - 24 months since first entry, 12 months since second entry		-188.46
		(241.34)
Total treatment - 36 months since first entry, 24 months since second entry		-509.85
		(448.38)
Price of gasoline (P_{Cum})		-47.86
		(38.99)
Price per unlinked passenger trip (P_{PTum})		-532.49***
		(180.17)
Public transportation mileage per capita ($Mile_{um}$)		223626***
		(71376)
Unemployment	Y	Y
Seasonal dummies	Y	Y
Urbanized area dummies	Y	Y
N	1798	1465

Notes: Dependent variable is then number of 10,000 unlinked passenger trips in month m in UZA u. Column (1) is an estimate of model (M1). Column (2) is an estimate of model (M2). Standard errors are in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 2: Share of UPT by Rail and Bus

UZA	Rail	Bus
Atlanta	0.511	0.489
Austin	0.022	0.978
Baltimore	0.277	0.723
Boston	0.684	0.316
Charlotte	0.185	0.815
Chicago	0.467	0.533
Columbus	0.000	1.000
Dallas	0.400	0.600
Denver	0.228	0.772
Detroit	0.040	0.960
Houston	0.167	0.833
Indianapolis	0.000	1.000
Jacksonville	0.076	0.924
Los Angeles	0.177	0.823
Milwaukee	0.000	1.000
Minneapolis-St. Paul	0.147	0.853
Nashville	0.027	0.973
New York	0.703	0.297
Oklahoma City	0.000	1.000
Philadelphia	0.485	0.515
Phoenix	0.194	0.806
Pittsburgh	0.123	0.877
Providence	0.000	1.000
Sacramento	0.429	0.571
San Diego	0.390	0.610
Seattle	0.081	0.919
Honolulu	0.000	1.000
Washington, DC	0.607	0.393

Table 3: Explaining monthly unlinked passenger trips by rail and bus in a urban area

	Rail UPT only		Bus UPT only	
Model Specification	(1)	(2)	(3)	(4)
First entrant treatment (ρ_F)	108.5***	70.6	15.87	26.47
	(35.36)	(54.83)	(13.09)	(21.12)
First entrant treatment - 12 months since entry		-118.45		89.39*
		(123.18)		(46.87)
First entrant treatment - 24 months since entry		-173.55		197.01**
		(247.38)		(93.57)
First entrant treatment - 36 months since entry		-94.7		349.33**
		(421.21)		(159.31)
Second entrant treatment (ρ_S)	-194.95***	-22.67	20.26	-52.31**
	(34.16)	(58.62)	(12.59)	(22.6)
Second entrant treatment - 12 months since entry		-141.6		-146.89***
		(87.07)		(33.7)
Second entrant treatment - 24 months since entry		-446.44*		-384.43***
		(252.85)		(102.5)
Second entrant treatment - 36 months since entry		-937.19		-764.93***
		(662.06)		(271.17)
Total Treatment ($\rho_F + \rho_S$)	-86.44**		36.14**	
	(42.8)		(14.96)	
Total treatment - 12 months since first entry, 0 months since second entry		-141.12		37.08
		(127.63)		(47.62)
Total treatment - 24 months since first entry, 12 months since second entry		-315.15		50.13
		(236.79)		(87.07)
Total treatment - 36 months since first entry, 24 months since second entry		-541.14		-35.1
		(431.97)		(161.74)
Price of gasoline (P_{Cum})		-102.16***		66.49***
		(35.42)		(14.11)
Price per unlinked passenger trip (P_{PTum})		-60.43		-121.45*
		(51.58)		(71.21)
Rail or Non-Rail mileage per capita ($Mile_{um}$)		744113.4		-26616.74
		(2627639)		(25630.09)
Unemployment	Y	Y	Y	Y
Seasonal dummies	Y	Y	Y	Y
Urbanized area dummies	Y	Y	Y	Y
N	1405	1153	1798	1465

Notes: Dependent variable is then number of 10,000 unlinked passenger trips in month *m* in UZA *u* on buses only or trains only. Columns (1) and (3) are estimates of model (M1). Columns (2) and (4) are estimates of model (M2). Standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Supplementary Information

SI File A

Certain changes in best-practices of public transportation data collection may impact the results. In January 2012, certain UZA-level agencies shifted from reporting UPT on a monthly basis to an annual basis. These agencies are known as "reduced reporters." During the year FTA calculates monthly UPT for reduced reporters by dividing the ridership figures reported for the previous annual report year by 12. UPT figures for reduced reporters are than corrected once the agency submits data at the end of the year. Therefore, reduced reporting only affects our 2016 UPT data. Further, our UPT numbers for UZA *u* in month *m* are the sum of all agency UPTs for that month. Agencies are eligible for reduced reporting only if they have thirty or fewer vehicles. In most UZA any reduced reporter contributes a minimal amount to the UZA's monthly UPT. Therefore, whatever measurement error reduced reporting adds to 2016 UPT_{um} data will not substantially affect our results.

For the data and code used to estimate the regression models see http://www.bowdoin.edu/faculty/enelson/research-data-files/UberLyftData.zip

SI Table A: Public Transportation by Mode

Abbreviation	Mode of Service
AG	Automated Guideway
CB	Commuter Bus
CC	Cable Car
CR	Commuter Rail
DR	Demand Responsive Paratransit
DT	Demand Responsive Paratransit - Taxi
HR	Heavy Rail
IP	Inclined Plane
LR	Light Rail
MB	Bus
MG	Monorail/Automated Guideway
MO	Monorail
RB	Bus Rapid Transit
SR	Streetcar Rail
TB	Trolleybus
VP	Van Pool
YR	Hybrid Rail

SI Table B: The date of the first and second ride-hailing company across the 28 UZAs considered in this study. See SI Table C for the sources of this entry data.

Official UZA name	Short hand for UZA	First Entry		Second Entry	
		Month	Year	Month	Year
Atlanta, GA	Atlanta	8	2012	8	2013
Austin, TX	Austin	6	2014	6	2014
Baltimore, MD	Baltimore	1	2013	10	2013
Boston, MA--NH--RI	Boston	10	2011	5	2013
Charlotte, NC--SC	Charlotte	9	2013	9	2013
Chicago, IL--IN	Chicago	9	2011	5	2013
Columbus, OH	Columbus	12	2013	2	2014
Dallas--Fort Worth--Arlington, TX	Dallas	9	2012	10	2013
Denver--Aurora, CO	Denver	9	2012	9	2013
Detroit, MI	Detroit	3	2013	4	2014
Houston, TX	Houston	2	2014	2	2014
Indianapolis, IN	Indianapolis	6	2013	8	2013
Jacksonville, FL	Jacksonville	12	2013	4	2014
Los Angeles--Long Beach--Santa Ana, CA	Los Angeles	3	2012	2	2013
Milwaukee, WI	Milwaukee	3	2014	4	2014
Minneapolis--St. Paul, MN	Minneapolis-St Paul	10	2012	8	2013
Nashville-Davidson, TN	Nashville	12	2013	12	2013
New York--Newark, NY--NJ--CT	New York	5	2011	7	2014
Oklahoma City, OK	Oklahoma City	10	2013	4	2014
Philadelphia, PA--NJ--DE--MD	Philadelphia*	6	2012	2	2015
Phoenix--Mesa, AZ	Phoenix	11	2012	9	2013
Pittsburgh, PA	Pittsburgh	2	2014	3	2014
Providence, RI--MA	Providence	9	2013	3	2014
Sacramento, CA	Sacramento	1	2013	11	2013
San Diego, CA	San Diego	6	2012	7	2013
Seattle, WA	Seattle	8	2011	4	2013
Honolulu, HI	Honolulu*	8	2013	6	2015
Washington, DC--VA--MD	Washington, DC*	12	2011	11	2015

Notes: Dropped from regression analysis due to insufficient UPT data post-second entry. In every case besides Pittsburgh the second entrant was Lyft.

SI Table C: List of websites that provided date of entry into each UZA in SI Table B

City	State	Uber Launch Source	Lyft Launch Source
Atlanta	GA	https://newsroom.uber.com/us-georgia/uber-atlanta-launches-spottieottiedopaliscious/	https//www.cnet.com/news/lyft-launches-in-indianapolis-st-paul-atlanta/
Austin	TX	http://kxan.com/2014/06/04/uber-launches-in-austin-despite-official-ban/	http://www.siliconhillsnews.com/2014/05/30/lyft-launches-in-austin-without-city-approval/
Baltimore	MD	https://newsroom.uber.com/us-maryland/baltimore-ubereverywhere/	http://blog.lyft.com/posts/2013/10/17/bringing-lyftlove-to-baltimore?rq=launch
Boston	MA	https://newsroom.uber.com/us-massachusetts/uber-bahsstuhn-is-live/	http//blog.lyft.com/posts/2013/5/31/lyft-lands-on-the-east-coast?rq=launch
Charlotte	NC	https://newsroom.uber.com/us-north-carolina/uber-gets-a-royal-welcome-back-to-the-queen-city/	http://flygracefully.boardingarea.com/2013/09/18/uber-and-lyft-have-launched-in-charlotte-sidecar-coming-soon/
Chicago	IL	https://newsroom.uber.com/us-illinois/chicago-ubers-biggest-launch-to-date/	http//blog.lyft.com/posts/2013/5/9/ready-for-lyft-off-in-chicago-and-beyond?rq=launch
Dallas	TX	https://newsroom.uber.com/us-texas/uber-does-dallas/	http//blog.lyft.com/posts/2013/9/27/lyft-gallops-into-dallas?rq=launch
Denver	CO	https://newsroom.uber.com/us-colorado/denver-launch-sky-high-in-the-mile-high-city/	http//blog.lyft.com/posts/2013/9/26/lyft-reaches-new-heights-in-denver?rq=launch
Detroit	MI	http://palminteractive.com/uber-quietly-launches-in-detroit-heres-a-20-promo-code-to-try-it/	http://blog.lyft.com/posts/lyft-powers-into-the-motor-city?rq=launch
Houston	TX	http://www.chron.com/news/houston-texas/houston/article/Ridesharing-service-Uber-jumps-into-Houston-market-5253892.php	https://www.facebook.com/events/1455826387968560/
Indianapolis	IN	https://newsroom.uber.com/us-indiana/hi-indianapolis-your-uber-is-arriving-now/	https://www.cnet.com/news/lyft-launches-in-indianapolis-st-paul-atlanta/
Jacksonville	FL	https://eujacksonville.com/2013/12/02/uber/	https://techcrunch.com/2014/04/24/lyft-24-new-cities/
Los Angeles	CA	https://newsroom.uber.com/us-california/uber-la-officially-launched/	http//blog.lyft.com/posts/2013/1/30/la-were-ready-for-lyft-off?rq=launch
Milwaukee	WI	https://newsroom.uber.com/us-wisconsin/uberx-has-arrived-in-mke-in-time-for-opening-day/	http://blog.lyft.com/posts/2014/4/11/the-pink-mustache-arrives-in-milwaukee?rq=launch
Minneapolis-St. Paul	MN	https://newsroom.uber.com/us-minnesota/minneapolisst-paul-ubereverywhere/	https//www.cnet.com/news/lyft-launches-in-indianapolis-st-paul-atlanta/
Nashville	TN	https://newsroom.uber.com/us-tennessee/nashville-uberx-better-cheaper-faster-than-a-taxi/	http://blog.lyft.com/posts/lyft-rolls-into-nashville?rq=launch
New York City	NY	https://newsroom.uber.com/uber-nyc-launches-service/	http//blog.lyft.com/posts/2014/7/8/lyft--in-new-yorks-outer-boroughs?rq=launch http://blog.lyft.com/posts/2014/7/25/lyft-launches-in-nyc?rq=launch
Oklahoma City	OK	https://newsroom.uber.com/us-oklahoma/ubers-are-hitting-the-roads-of-	https://techcrunch.com/2014/04/24/lyft-24-new-cities/

City	State	Uber Launch Source	Lyft Launch Source
		okc-yall/	
Philadelphia	PA	http://philly.curbed.com/2012/6/6/10364976/today-uber-launches-in-philly-even-though-we-dont-it-here	http//blog.lyft.com/posts/philadelphia?rq=launch
Phoenix	AZ	http://aztechbeat.com/2012/11/uber-launches-its-on-demand-driving-service-publicly-in-phoenix/	http://blog.lyft.com/posts/2013/9/6/lyft-is-heating-up-in-phoenix?rq=launch
Pittsburgh	PA	https://newsroom.uber.com/us-pennsylvania/uber-officially-launches-in-pittsburgh/	https://c-leveled.com/lyft-pittsburgh/
Providence	RI	https://newsroom.uber.com/us-rhode-island/happy-3-year-rhode-island/	http://blog.lyft.com/posts/providence-warm-fuzzy-rides-coming-your-way?rq=launch
Sacramento	CA	https://sacramentopress.com/2013/01/30/uber-car-service-launches-in-sacramento/	http://blog.lyft.com/posts/2014/4/29/mayor-kevin-johnson-welcomes-lyft-to-sacramento?rq=launch
San Diego	CA	https://newsroom.uber.com/us-california/san-diego-launch/	http//articles.latimes.com/2013/jul/02/business/la-fi-tn-lyft-san-diego-los-angeles-20130702
Seattle	WA	https://newsroom.uber.com/us-washington/you-are-now-free-to-move-about-seattle/	http//blog.lyft.com/posts/2013/4/11/lyft-sails-into-seattle?rq=launch
Honolulu	HI	https://newsroom.uber.com/us-hawaii/uber-launches-in-honolulu-with-a-splash/	http://blog.lyft.com/posts/2014/6/4/pack-your-bags-lyft-says-aloha-to-honolulu?rq=launch
Washington, DC	DC	http://www.greencarreports.com/news/1077654_uber-app-to-connect-riders-and-drivers-now-legal-in-d-c-at-last	http//blog.lyft.com/posts/dc-lyft-line?rq=launch